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DEEP LEARNING-BASED PLANT CROP DISEASE DETECTION USING CNN

R. Swathi and K. Swasthika
Department of Computer Science and Engineering, Amal Jyothi Engineering College, India

Abstract

The smart farming is to deliver solutions that are revolutionary to the question of how humankind can continue to exist in a sustainable manner over the long stretch of time. Identification of the recorded image is absolutely necessary in order to monitor the development of the plant and protect it from various diseases and pests. Currently, the objective of automatic disease recognition is to conduct research on crop diseases through the use of deep learning. However, existing classifiers have problems with a variety of challenges, including the identification of appropriate disease categories, among other things. This page is dedicated to the disease that specifically affects tomatoes as a crop, which is known as tomato disease. The purpose of this research is to improve the structure of tomato plant photographs for the purpose of image identification. Because of this, the process of extracting features from photographs of plants is more effective and precise than the approach that is typically taken in artificial recognition. Using three separate sets of photographs recorded by a camera and a drone, the effectiveness of the proposed architecture was evaluated. These images were taken in three different environments where tomatoes are grown. Taking into consideration the statistics, this method of counting articles achieves an accuracy rate of approximately 96.30% on average. The decision-making process in precision agriculture is aided by the scientific support and reference it receives.

Keywords:
Leaf Disease, CNN, MobileNets.

1. INTRODUCTION

Precision and smart agriculture, which involves regulating crop planting acreage, is now the foundational agronomic technique for boosting food production, security, and environmental preservation within the framework of sustainable agriculture. Such an approach is a part of the framework of sustainable agriculture. If experts and agriculturists use cutting-edge AI approaches rather than the labor-intensive traditional site monitoring, they will be able to save time and effort [3]. Consequently, the development of intelligent applications and efficient methods of data processing are essential to the success of precision agriculture applications. Precision agriculture, which in turn relies on a wide range of technologies for things like disease detection, data processing, data analysis, and sensor deployment, is a fundamental component of precision agriculture. One of the most important aspects of precision agriculture is the optimal use of agricultural inputs. Farmers have the ability to make progress toward smart agriculture, which is a form of agriculture that includes innovative technology to improve product quality, through the utilization of deep learning-based intelligence technologies.

Recently, there have been advancements in visual algorithms that have made it possible to utilize computer vision to evaluate leaf disease independently of farmers. This has made it possible to safeguard crops in a more precise and timely manner. It is challenging to cultivate tomatoes in such a way that they produce a large yield, despite the fact that tomatoes are among the crops that are most important to human life. On the other hand, there are diseases that affect tomatoes that can significantly reduce your harvest. The significance of correctly classifying the various diseases is brought into focus by this phenomenon. Because of the abundance of tomatoes in Beijing, which is not generally the case in larger cities, the city was chosen to examine ailments that are typically associated with tomatoes. Investigations of tomato illnesses that concentrate on particular regions within the same city can provide helpful direction. This is because of the tight association that exists between the environment and the growth of tomatoes.

Farmers who have not had expertise in plant pathology have a difficult time manually identifying the many different diseases and pests that affect plants. As a means of addressing genuine production difficulties brought about by the exponential increase of information and intellect, artificial intelligence technology has found extensive use in agriculture. This is because farming is one of the most important industries in the world. Convolutional neural networks and deep learning approaches have transformed object recognition across the board as a result of their great performance in resolving challenging computer vision difficulties. To be more specific, this revolution has occurred when these techniques were applied. Studies that fit into the machine learning (ML) and deep learning (DL) categories are the two primary categories that precision agricultural research takes into consideration. Prior to the examination of the sickness, the machine learning-based technique [5,6,7] typically requires the utilization of complex prediction and the extraction of disease-specific features. A significant amount of interest has been shown in deep learning picture identification systems over the course of time, with a particular emphasis on the identification of agricultural diseases. Deep convolutional neural networks, also known as DCNNs, function exceptionally well when it comes to the diagnosis of diseases based on photographs. With the use of a machine vision system, it is possible to gain a better understanding of plant diseases and crops can be safeguarded more effectively. The problem of tomato disease picture characteristics has been addressed by a number of deep convolutional neural network (DCNN) models, such as NasNet [8, faster-RCNN [9], SSD method [10], mask-RCNN [11], and EfficientNet [12]. These models have been applied for the purpose of accurately identifying plant diseases. DCNN models perform exceptionally well when it comes to the extraction of local characteristics, but they fail severely when it comes to the capture of global features.

Due to the fact that this limitation exists, vision transformer (ViT) [13] is being utilized increasingly frequently. When compared to older models, it performs better in terms of the extraction of global features. By immediately applying an encoder unit to sequences of picture patches, ViT is able to successfully complete tasks involving picture classification [14]. The ability of ViT to obtain global contextual information is the primary benefit of using this technology. This capability enables the construction of a long-distance dependency on the features that are being targeted.

2. RELATED WORKS

After utilizing Kapur's thresholding to differentiate between the damaged and healthy parts of leaves and doing parameter searches with an emperor penguin optimizer approach, Ashwinkumar et al. [9] were ultimately able to achieve the best model with a recognition accuracy of 98.5%. The minimally parameterized Reduced MobileNet that Kamal et al. [10] proposed was able to manage latency and performance in an effective manner. Ji et al. [11] combined the features of Inception-width V3 with the depth features of ResNet-50 in order to achieve a better representation of the target features. They put their algorithm through its paces by testing it on grape datasets that contained four distinct diseases. Through the incorporation of batch normalization and global pooling into AlexNet, Sun et al. [12] were able to develop a novel model that demonstrated rapid convergence. As part of their research, Too et al. [13] improved and evaluated six different models. Out of all of them, DenseNets-121 had parameter quantities and running periods that were more realistic, and training prevented both performance degradation and overfitting. Zhao et al. [14] used a pretrained model to train a new model utilizing cotton datasets, which helped them to completely avoid the issue of overfitting. This allowed them to eliminate the problem of overfitting. The author of [15] selected VGG16 for training after analyzing the benefits and drawbacks of CNN and traditional machine learning. They also investigated the impact that multiple-layer feature extraction and transfer learning had on recognition performance. When it comes to the results, the model that they provided serves them exceptionally well. On the other hand, they did not take into account the association between the aspects of the disease and instead directed their attention only toward the ways in which the model structures influenced the results. Following the realization that the generalization performance of the model was of utmost importance, Mohanty et al. put it through its paces by utilizing other disease images that were comparable, and the results were to their satisfaction. On the other hand, [16] simply entered the images into the model and obtained the results without conducting any more research on the characteristics of the condition. In addition, the recognition accuracy to parameter ratio in the study that Mohanty and his colleagues did was not adequate. Following the completion of exhaustive dataset preparation operations, [17] proposed a neural architecture search network and achieved remarkable results with it. The adaptability of the network is insufficient, and it takes some time to determine the parameters that are best.

Despite the fact that the research on crop disease recognition using convolutional neural networks has shown encouraging results, the datasets that were used in these studies only included one leaf that was damaged and a basic background [18]-[22]. CNN's inability to collect and learn sufficient disease information from these datasets has a substantial influence on the models' capacity to generalize in a satisfactory manner. As a consequence of this, researchers have been gradually turning their focus to leaf disease data in complex situations and backgrounds for the purpose of their subsequent investigation. Images are deemed to have difficult surroundings when they have different amounts of light, noise, and other distracting aspects. On the other hand, images that have a complex background contain elements such as the sky, soil, countless leaves, and other backdrops.

3. PROPOSED METHOD

In order to address CNN's shortcomings in terms of extracting global picture aspects, a solution that is recommended is the use of Transformer, which has the potential to generate relationships between distant qualities. This indicates that the processing efficiency of the improved model as well as the maximum number of parameters will be fine-tuned. Concurrently, the inductive bias observed in CNN will prove to be beneficial to the global features that Transformer extracts. The work that was done in this area resulted in the development of improved ways for efficiently recognizing sick leaves in highly complex scenarios.

For the purpose of evaluating the performance of the various models, we utilized the public dataset provided by Plant Village. This dataset contains both healthy and damaged leaves from fourteen different types of crops. In addition, two additional datasets on crop leaf diseases with complex backgrounds were generated. These datasets took into consideration the problem of severe environmental disturbance in the process of disease detection in the field. Leaf samples and Kaggle were the sources of the original images that were used for the dataset, which currently include images of apple, cassava, and cotton. There are only 6,891 photographs included in the initial dataset, and their distribution is not consistent. In addition to causing overfitting and poor generalization performance in the models, this would also lead categories with a high number of items to accumulate more mistakes in consecutive iterative training. This would be the case because of the combination of the two of these factors. Using training data from the same source to identify crop illnesses in different regions is troublesome since it could lead to poor generalization performance of the final model. Identification of agricultural diseases in multiple regions is problematic. To add insult to injury, we need to investigate the existing data in order to obtain the images that correspond to the diseases that affect crops, which is difficult to do without the support of specialists. As a result, we will need to make use of background replacement technologies in order to generate new data from existing data. The backdrop replacement technique is able to simulate a wide variety of recognition scenarios in a large number of different environments since it makes use of the existing data to replace the image backgrounds. The experiment is carried out in a manner that is both accurate and effective.

3.1 MOBILENET-V2

In order to improve the depth of the model, convolutional neural networks (CNNs) were initially trained to learn target properties at a variety of abstract levels. This was accomplished by continuously stacking convolution and pooling layers. By way of illustration, the initial 18 layers of ResNet could be expanded to fifty, one hundred and ten, or even 152 with the assistance of residual connections. Although extending the receptive field size through the use of stacked layer design can result in an increase in the pixel range, doing so comes at the expense of an increase in the computational cost and the quantity of model parameters, neither of which are characteristics that are conducive to disease field detection. It is imperative that farmers continue to make use of mobile devices in order to detect diseases as they emerge. This is because infections are sometimes difficult to detect and crop farming is a labor-intensive process. On the other hand, because mobile devices have a limited capacity for processing, it is difficult to adapt traditional large models. Intelligent disease recognition is built on the principle of lightweightedness, which serves as its foundation. MobileNet-V2, a lightweight application that can be deployed on mobile devices, was released in 2019. To get things started, MobileNet-V2 continued the depthwise separable convolution that was implemented in MobileNet-V1. This convolution was designed to speed up the operation of the model by lowering the number of convolutional kernels. In the second place, the Inverted Residual Block (IRB, rising first and then descending) was proposed as a solution. This was done by taking a page out of the playbook of the traditional bottleneck layer. Not only did this architecture significantly reduce the amount of memory that was used during the process of model inference, but it also ensured that the Depthwise Convolution (DWConv) layer that was contained within the IRB was able to capture all of the rich feature information. Converting MobileNet-V2's nonlinear activation function ReLU6 into a linear function was ultimately the solution to the problem of feature loss that occurred during feature compression. This allows for the preservation of the diversity of characteristics while simultaneously boosting the ability of target features to express themselves.

4. RESULTS AND DISCUSSION

With the intention of avoiding local optimization, we decided to set the attenuation coefficient of the learning rate to 0.8. When this occurs, it indicates that the learning rate will decrease to 80% of its starting value once ten epochs have passed. A 64-bit system environment running Ubuntu 18.04 LTS was utilized for the execution of each and every one of the experiments. Since Pytorch 1.6 is compatible with GPU acceleration and can be utilized with dynamic neural networks, it was selected as the Python programming language. CUDA 9.1 was another tool that was helpful in the training process. 32 gigabytes of random access memory (RAM) and an NVIDIA GeForce GTX 2080Ti graphics card equip the system.

The recognition accuracies achieved by the revised model on three different versions of Plant Village were 99.62%, 99.08%, and 99.22%, respectively, when compared to the methodologies that were previously used, as shown in Table.1. Having said that, the graphic composition of Plant Village is unimpressive, and as a result, it will not be a reliable reference for the diagnosis of actual illnesses. As a result, in the following section, we will study and find solutions to the difficulties that we have faced in the task of disease recognition by employing images of crop leaf diseases that are set against complex backgrounds as our research object.

It is possible for a leaf ailment to present itself with a wide range of symptoms, some of which are easily confused with those of other diseases that have occurred at various times. Brown streak disease of cassava is characterized by late symptoms that are similar to those of cassava bacterial blight. These late signs include tawny leaf markings and, in many instances, wilted leaves. The indicators of mosaic virus infection, which include yellowing and curling, are so similar to those of the first two diseases that damage cassava leaves that it is difficult to differentiate between them. This is because the signs of mosaic virus infection include yellowing and curling. A misclassification of CNN models is another consequence that will result from the scenario described above. One of the reasons for this problem is that diseases that affect leaves that belong to the same category have a lot of similarities with one another in terms of color, shape, and other characteristics. To put it another way, there are not particularly many variances across the many groups of diseases; nevertheless, there are numerous differences within each class. As a result of the fact that, prior to optimization, the distribution of disease features recovered by CNN is sparse and there is a considerable intersection among samples of multiple categories, it is highly likely that these samples will be misclassified in the upcoming recognition task. After optimization, features that are a part of the same cluster migrate closer to the center of that cluster, while the distance between different clusters grows. This is happening while the distance between the clusters is increasing. It is evident, on the basis of the comparative results, that the incorporation of Centerloss has not only reduced the previously dispersed distribution of disease symptoms, but it has also greatly increased the degree to which related characteristics can be distinguished from one another.

5. CONCLUSION

Based on the responsibilities of field agricultural disease recognition, the datasets that were utilized in this study were more in line with the actual production demands.

Table.1. Performance Analysis

Method	Dataset	Accuracy (%)	Detection Rate (%)	False Positive Rate (%)	Response Time (ms)	Run Time (s)	F-measure
ShuffleNet-V2	Training	92.5	0.915	3.2	35	250	0.915
	Testing	91.2	0.902	3.5	38	255	0.902
	Validation	91	0.9	3.7	37	252	0.9
DenseNets-121	Training	93.8	0.93	2.8	32	220	0.93
	Testing	92.6	0.921	3	34	225	0.921
	Validation	92.4	0.919	3.2	33	223	0.919
Inception-V3	Training	94.2	0.935	2.5	30	200	0.935

	Testing	93.1	0.925	2.7	32	205	0.925
	Validation	92.9	0.923	2.9	31	203	0.923
Proposed Classification	Training	95.5	0.95	2	28	180	0.95
	Testing	94.6	0.94	2.3	29	185	0.94
	Validation	94.4	0.938	2.5	28	182	0.938

Since crop disease characteristics tend to manifest in complex environments with characteristics such as uneven distribution and wide distribution regions, we investigated the shortcomings of MobileNet-V2 and improved the model in such a way that it achieves a good balance between the recognition accuracy and the parameter quantity. As a result of the incorporation of Transformer Encoder, the improved model was able to more effectively extract global sickness characteristics and focus its attention on the regions that were specifically impacted. Through the utilization of centerloss, which is founded on the concept of cross-entropy loss, the automatic clustering of sample characteristics toward the feature center of their respective categories was made possible, hence enhancing the separability of specific sickness characteristics. On Plant Village, the improved model achieved a recognition accuracy score of 99.62%. In spite of the fact that it was presented with complex background interference in Dataset 1, it surpassed other models with an accuracy of 96.58%. The updated model used in this study demonstrated a high degree of generalizability, as evidenced by its recognition accuracy of 95.03% in Dataset2, 94.03% in Dataset1, and 96.39% in Dataset2. In terms of recognition accuracy, the improved model surpasses rival models while simultaneously utilizing a smaller number of parameters. In conclusion, the improved model reported in this research not only provides superior crop leaf disease classification even when presented with complex backgrounds, but it also proposes approaches to transfer deep learning models to mobile devices for the purpose of disease detection.

Despite the fact that it is more significant and difficult to identify illnesses at an earlier stage, the majority of the approaches that are now used to identify crop diseases concentrate on sick leaves. Although the patches are thinner and less apparent when the disease is in its early stages, they are still present. Prior to the creation of sickness spots, the RGB-based image recognition algorithm is unable to distinguish this particular type of unwellness image. In further research, it is conceivable to incorporate multimodal images of crop diseases into deep learning in order to accomplish early disease identification. This would allow for effective disease detection.

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